# APPLICATION OF FUZZY LOGIC TO MODEL TRIP GENERATION PHASE OF SEQUENCIAL TRAVEL DEMAND ANALYSIS

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A

Project Report

On

# APPLICATION OF FUZZY LOGIC TO MODEL TRIP GENERATION PHASE OF SEQUENCIAL TRAVEL DEMAND ANALYSIS

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# CERTIFICATE

It is certified that the work contained in the thesis entitled **"*Application of fuzzy logic to model trip generation phase of sequential travel demand analysis*"** submitted by ***Mr.Abhishek Agarwal (Roll No.-108CE008)***, has been carried out under my supervision and this work has not been submitted elsewhere for a degree.

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# ABSTRACT

Sequential travel demand analysis consists of four phases, namely, trip generation, trip distribution, modal split and route assignment. Although, the later three phases are supported with quite sufficient number of efficient models; the first one, i.e., trip generation being completely based on human decision making is not supported with any efficient model. Existing models on trip generation are deterministic in nature and cannot capture the inherent vagueness of human mind regarding trip choice. Generally, the models of trip-generation include variables which reflect the number of potential trip-makers and the propensity of potential trip-makers to make a trip. However, none of the present models incorporate variables which reflect the accessibility factor. This is possibly the single largest factor as to why trip-generation models cannot very well predict the number of trips generated. It is intended to apply fuzzy logic, which is a linguistic tool to capture the imprecise nature of human mind regarding trip decision. Also, existing models on trip generation do not cover important premise variables controlling trip generation. In the proposed model it is intended to embed it properly.

To validate the developed model empirical data is used.

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# Chapter-1

# Introduction

Travelling seems to play an important and increasingly larger role in our life-style. Accidents, congestions, delay are the principal problems associated with the use of transportation. As a result an understanding of the underlying behaviour involved in trip making, i.e., movements from origin to destinations performed by people on a daily basis, becomes very essential for a society to take effective steps in areas of transportation infrastructures, management and land use, etc. Generally, sequential travel demand analysis is used in forecasting the travel demand.[1]

Sequential travel demand analysis consists of four stages, namely, trip generation, trip distribution, modal split and route assignment. The Trip generation stage aims at predicting the total number of trips generated and attracted to each zone of the study area. From the data on household and socio-economic attributes, this stage answers the question to "how many trips" originated from a particular zone.[2]

## 1.1 Types of trip

The word "trip" is defined as an outward and return journey from a point of origin to a point of destination. If the trip-maker's home is either origin or destination of the trip, then such trips are known as home based trips and the rest as non-home based trips. All the trips of home based and non-home based together give the total trip production. Figure 1 shows the home and non-home based trips.

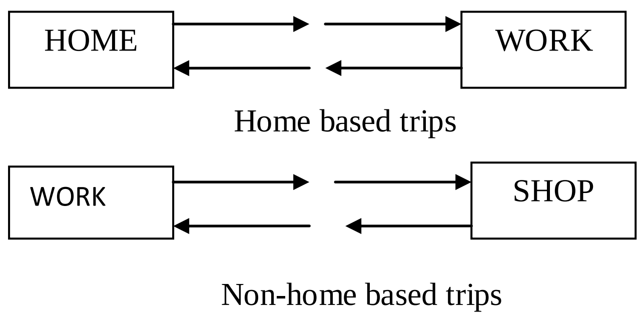


Figure 1: types of trips

Trips can also be classified as trip purpose, trip time of the day and by the person type. Based on the purpose of the journey trips can be classified as trips for shopping, trips for education, trips for work, trips for recreation and other trips. 80 to 85 percent of the above trips constitute of the home based trips. Non-home based trips, being a small portion are not normally treated separately. Based on the time of the day when the trips are made, trips are classified as peak trips and off-peak trips. Another way of classification is based on the individual who makes the trip. Since, the travel behaviour is highly influenced by the socio-economic attributes of the individual trips are categorised based on the income level, vehicle ownership and household size.

## 1.2 Factors affecting trip generation

The main factors which affect the trip generation of a particular zone are the number of potential trip-makers in the zone and the propensity of a potential trip-maker to make a trip. These data could be captured by variable like age distribution of the occupants, income level, vehicle ownership, household structure and family size.[2]

There are basically two different model structures for the trip-generation models.

## 1.3 The cross-classification model

It is also referred to as the category-analysis model and is based on the assumption that the number of trips generated by similar households belonging to the same category is same. According to this model, if in zone $i$ there are $n_k^i$ households in category $k$ and if $g_k$ is the average rate of trip-generation per household in category $k$ then the relation for trips generation by zone $i, T_i$, is given by[2]

$$T_i = \sum_{\forall k} n_k^i \, g_k \tag{1}$$

The total number of trips produced by a zone is predicted simply by aggregating the total trips produced by all the households in that zone. The various categories of houses and the rate of trip-generation for a given category of households are determined through empirical; observations and analysis.

## 1.4 Regression model

This model assumes an additive functional form exists between the factors which effect trip-generation and the number of trips generated. A linear function of the following form is generally used [2]

$$T_i = \alpha_1 z_{1,i} + \alpha_2 z_{2,i} + \cdots + \alpha_n z_{n,i} + U \tag{2}$$

Where $\alpha_k$ are the parameters of the regression function, U is the disturbance terms and is a constant and $z_{k,i}$ is the value of the $k$th variable, such as income, automobile ownership, number of members in a household etc., for the $i$th zone. The parameters are determined by using some parameter estimation techniques such as Ordinary Least Square or Maximum Likelihood Technique on empirically obtained data on $z_k$ variables and $T_i$.

## 1.5 Benefits of Fuzzy Logic Application

Both these models are mathematical models and they rely on study of the empirical data. Moreover they do not take into account the vagueness of the human mind and the uncertainties associated with trip making. Fuzzy logic, being a linguistic tool is capable of incorporating the vagueness of the human mind and thus give better results than the above two models. When the prevailing conditions are not clear and the consequences of the course of action are not known, it can determine the course of action.

# Chapter-2

# Literature Review

## 2.1 Applications of Fuzzy Logic in Transportation Engineering

The fuzzy rule based inference system has been recognized as a useful approach to model many complex phenomena in the field of transportation engineering.[7] In the past few decades a large number of deterministic and/or stochastic models have been developed to solve complex traffic and transportation engineering problems. These mathematical models use different formulae and equations to solve such problems. However, when solving real-life engineering problems, linguistic information is often encountered that is frequently hard to quantify using `classical' mathematical techniques. [4] The first application to transportation was introduced by Pappis and Mamdani (1977) on fuzzy controlled traffic signal, and they set the stage for not only the practical mathematical operations of fuzzy inference but also opened the door to various transportation applications. [8] Perhaps the most significant milestone was the successful real world application to the control of subway vehicles in Sendai, Japan (Sugeno, 1989).[10]

Basic results linked to the development of fuzzy logic date from Zadeh (1973) and Mamdani and Assilian (1975).[4] Introducing a concept he called `Approximate Reasoning', Zadeh successfully showed that vague logical statements enable the formation of algorithms that can use vague data to derive vague inferences.[6] Zadeh assumed his approach would be beneficial above all in the study of complex humanistic systems. Realizing that Zadeh's approach could be successfully applied to industrial plant controllers, Mamdani and Assilian

(1975) applied this method to control a pilot-scale steam engine.[11] They used fuzzy logic in order to express linguistic rules. Pioneer papers in the field of fuzzy controllers include Mamdani (1974), Kickert and van Nauta Lemke (1976), Ostergard (1976), and Tong (1976). Tong (1977) made a control engineering review of fuzzy systems. Regarding the application of fuzzy logic in engineering, the tutorial given by Mendel (1995) is of utmost importance, as is the recently published book by Ross (1995).[4]

## 2.2. Trip Generation

Trip generation problem was solved using fuzzy logic by Kalic' and Teodorovic' (1997b). The procedure proposed by Wang and Mendel (1992a) was used for the generation of fuzzy rule base by learning from numerical examples.[4] For this, the available set of data was divided into two subsets, one was used for the fuzzy rule base generation, and the other was intended to be a control data subset. The obtained fuzzy system was tested on both subsets of data after the creation of the fuzzy rule base. The number of trips for the subsets was also estimated using both artificial neural networks, and by multiple linear regressions. Simulated annealing technique was used for the training of the neutral network. The fuzzy logic approach proved to give the closest estimate of the actual number of trips generated in a given area.

Xu and Chan (1993a, b) were the first to use the fuzzy set theory techniques when analyzing the problems arising from the poor quality of link count data. Traffic counts are often subject to errors. Xu and Chan (1993a, b) particularly pointed out the problem of traffic counts in developing countries such as China in which mixed urban traffic flow with heavy bicycle volume is common. In such situations the heavy bicycle volume also makes precise vehicular counts very difficult. Xu and Chan (1993a, b) estimated an origin-destination matrix with fuzzy weights. [12, 13] They based their method on that of Chan et al. (1986) which was developed for a non-fuzzy case. [14]

# Chapter-3

## Empirical Calculations

In this section, the classical mathematical models of trip generation are applied to the field data collected. The field data used here is of NIT Rourkela Campus. A survey was conducted by the students of "Traffic and Transportation Engineering. Lab. (CE 702)" on 22-02-2012 inside the NIT Rourkela Campus and the data was collected from a total number of 127 households. The same data is used for empirical calculations using the classical mathematical models of trip generation. The vehicle ownership is converted to the PCU (Passenger Car Units) for the sake of uniformity. The household member are all 3 years and above. Children below 3 years of age are not considered. The tentatively equivalent factors of the Passenger Car Units (PCU) as in *Geometric Design Standards for Urban Roads in Plains* (IRC-83-1986) is given in table-1 below.[15]

Table 1: Passenger Car Equivalent Factors

| S.No. | Vehicle Type | Equivalency Factor |
|---|---|---|
| **1** | Passenger car, jeep,van,tempo,auto-rickshaw or agricultural tractors | 1.0 |
| **2** | Truck, bus or agricultural tractor-trailer | 3.0 |
| **3** | Motor-cycle, scooter and cycle | 0.5 |
| **4** | Cycle-rickshaw | 1.5 |
| **5** | Horse-drawn vehicle | 4.0 |
| **6** | Bullock-cart | 8.0 |
| **7** | Hand-cart | 6.0 |

## 3.1 Cross-Classification model

In this model, the empirical data is divided into different group based on the analysis of data. Tables are prepared that define homogenous household, i.e. households that are expected to produce same number of trips based of the characteristic of the household. The main difficulty faced in this model is of defining the categories correctly.

The data obtained from the 127 nos. of households is suitably divided into 4 groups namely,

- Low Income and Low Vehicle Ownership (LILV)
- Low Income and High Vehicle Ownership (LIHV)
- High Income and Low Vehicle Ownership (HILV)
- High Income and High Vehicle Ownership (HIHV)

For the LILV group, all the households having a monthly income equal or below ₹40,000 and vehicle ownership in terms of PCUs equal or below 1.5 are considered. The average number of trips/ week generated from the households is calculated. Table-2 below shows the households in LILV group and their average.

Table 2: List of households in LILV group

| Household no. | Income (₹) | No.of persons(>3years) | Vehicle Ownership (PCU) | No.of trips/week |
|---|---|---|---|---|
| 25 | 40000 | 6 | 0.5 | 12 |
| 26 | 40000 | 8 | 1.5 | 14 |
| 27 | 40000 | 5 | 1.5 | 35 |
| 28 | 40000 | 5 | 1.5 | 20 |
| 29 | 40000 | 8 | 1.5 | 18 |
| 31 | 40000 | 4 | 1.5 | 16 |
| 32 | 40000 | 4 | 1 | 14 |
| 34 | 40000 | 5 | 1.5 | 14 |
| 37 | 40000 | 4 | 1.5 | 18 |
| 38 | 40000 | 5 | 1.5 | 14 |
| 39 | 40000 | 5 | 1.5 | 18 |

| Household no. | Income (₹) | No.of persons(>3years) | Vehicle Ownership (PCU) | No.of trips/week |
|---|---|---|---|---|
| 40 | 40000 | 3 | 1.5 | 18 |
| 41 | 40000 | 5 | 1 | 18 |
| 43 | 40000 | 6 | 1 | 14 |
| 47 | 40000 | 4 | 1.5 | 30 |
| 50 | 40000 | 4 | 1 | 14 |
| 51 | 40000 | 5 | 1 | 14 |
| 52 | 40000 | 3 | 1 | 12 |
| 54 | 40000 | 5 | 1.5 | 20 |
| 56 | 40000 | 3 | 1.5 | 18 |
| 57 | 40000 | 5 | 1.5 | 24 |
| 59 | 40000 | 2 | 1.5 | 12 |
| 60 | 40000 | 4 | 1.5 | 24 |
| 61 | 40000 | 5 | 1 | 13 |
| 62 | 40000 | 4 | 1.5 | 19 |
| 63 | 40000 | 5 | 1 | 10 |
| 65 | 40000 | 5 | 1.5 | 15 |
| 66 | 40000 | 4 | 1.5 | 35 |
| 67 | 40000 | 4 | 1 | 30 |
| 68 | 40000 | 6 | 1 | 30 |
| 69 | 40000 | 4 | 1 | 25 |
| 72 | 40000 | 4 | 1 | 28 |
| 76 | 40000 | 4 | 1.5 | 26 |
| 81 | 40000 | 7 | 1.5 | 40 |
| 82 | 40000 | 2 | 1 | 20 |
| 84 | 40000 | 2 | 1 | 15 |
| 87 | 40000 | 4 | 0.5 | 15 |
| 88 | 40000 | 4 | 1 | 18 |
| 90 | 40000 | 3 | 1.5 | 18 |
| 91 | 40000 | 3 | 1 | 15 |
| 92 | 40000 | 5 | 1.5 | 20 |
| 95 | 40000 | 1 | 0.5 | 10 |
| 96 | 40000 | 4 | 1.5 | 16 |
| 97 | 40000 | 3 | 1 | 15 |
| 98 | 40000 | 4 | 1 | 14 |
| 100 | 40000 | 4 | 1.5 | 16 |
| 101 | 40000 | 5 | 1 | 20 |
| 103 | 40000 | 4 | 0.5 | 16 |
| 104 | 40000 | 4 | 1.5 | 18 |
| 105 | 40000 | 2 | 1 | 12 |
| 117 | 40000 | 3 | 1 | 11 |
| 118 | 40000 | 4 | 1 | 17 |
| 119 | 40000 | 2 | 1 | 17 |
| 120 | 40000 | 2 | 1 | 17 |
| 122 | 40000 | 4 | 1 | 10 |

| Household no. | Income (₹) | No.of persons(>3years) | Vehicle Ownership (PCU) | No.of trips/week |
|---|---|---|---|---|
| 123 | 40000 | 5 | 1 | 11 |
| 124 | 40000 | 4 | 1 | 11 |
| 126 | 40000 | 2 | 1 | 17 |
| 127 | 40000 | 4 | 1 | 12 |
| | | | Average no. of trips/week = | 18.01 |

Therefore, total number of household in the LILV category = 59

Similarly for LIHV group, all the households having a monthly income of below or equal to ₹40,000.00 and vehicle ownership in terms of PCUs greater than 1.5 are considered. The average no.of trips/week is also calculated. Table-3 below shows the households in the LIHV group and the calculations.

Table 3: List of households in LIHV group

| Household no. | Income (₹) | No.of persons(>3years) | Vehicle Ownership (PCU) | No.of trips/week |
|---|---|---|---|---|
| **30** | 40000 | 6 | 2.5 | 18 |
| **33** | 40000 | 10 | 2.5 | 41 |
| **35** | 40000 | 4 | 2.5 | 25 |
| **36** | 40000 | 8 | 2 | 19 |
| **42** | 40000 | 4 | 2.5 | 25 |
| **44** | 40000 | 8 | 2.5 | 31 |
| **45** | 40000 | 4 | 2.5 | 24 |
| **46** | 40000 | 3 | 2 | 16 |
| **48** | 40000 | 4 | 2 | 16 |
| **49** | 40000 | 4 | 2.5 | 18 |
| **53** | 40000 | 8 | 2.5 | 12 |
| **55** | 40000 | 5 | 2 | 28 |
| **58** | 40000 | 6 | 2.5 | 30 |
| **64** | 40000 | 5 | 2 | 13 |
| **70** | 40000 | 2 | 2 | 24 |
| **71** | 40000 | 4 | 2.5 | 25 |
| **73** | 40000 | 5 | 2 | 35 |
| **74** | 40000 | 7 | 3 | 40 |
| **75** | 40000 | 4 | 2 | 36 |
| **77** | 40000 | 4 | 3 | 27 |
| **78** | 40000 | 4 | 2 | 25 |
| **79** | 40000 | 4 | 2 | 38 |
| **80** | 40000 | 6 | 2 | 42 |

| Household no. | Income (₹) | No.of persons(>3years) | Vehicle Ownership (PCU) | No.of trips/week |
|---|---|---|---|---|
| **83** | 40000 | 6 | 2.5 | 25 |
| **85** | 40000 | 4 | 2 | 22 |
| **86** | 40000 | 4 | 2 | 25 |
| **89** | 40000 | 4 | 2 | 20 |
| **93** | 40000 | 5 | 2.5 | 30 |
| **94** | 40000 | 4 | 2 | 28 |
| **99** | 40000 | 4 | 2 | 18 |
| **102** | 40000 | 4 | 2.5 | 26 |
| **106** | 40000 | 4 | 2 | 50 |
| **107** | 40000 | 4 | 3 | 16 |
| **108** | 40000 | 3 | 2 | 30 |
| **109** | 40000 | 4 | 2 | 28 |
| **121** | 40000 | 5 | 2 | 18 |
| **125** | 40000 | 7 | 3 | 19 |
| | | Average no. of trips/week = | | 26.02 |

So, total number of households in the LIHV category = 37.

Similarly, for the HILV group the households having a monthly income of greater than ₹40,000.00 and vehicle ownership in terms of PCUs less than 1.5 are considered. The average no. of trips/week generated is also calculated. Table 4 below shows the data and the calculations.

Table 4: List of households in HILV group

| Household no. | Income (₹) | No.of persons(>3years) | Vehicle Ownership (PCU) | No.of trips/week |
|---|---|---|---|---|
| **1** | 80000 | 4 | 1.5 | 10 |
| **2** | 80000 | 2 | 0.5 | 13 |
| **4** | 80000 | 3 | 1.5 | 3 |
| **7** | 60000 | 4 | 1.5 | 17 |
| **20** | 60000 | 5 | 1.5 | 9 |
| **23** | 80000 | 2 | 1 | 22 |
| **24** | 80000 | 2 | 1.5 | 19 |
| **110** | 60000 | 5 | 0.5 | 12 |
| | | Average no. of trips/week = | | 13.12 |

Total number of households in the HILV category = 8

Similarly, for the HIHV group the households having a monthly income of greater than ₹40000 and having vehicle ownership in terms of PCUs more than 1.5 are considered. The average no. of trips/week is calculated. Table-5 in the next page shows the data and the calculations.

Table 5: List of households in HIHV group

| Household no. | Income (₹) | No.of persons(>3years) | Vehicle Ownership (PCU) | No.of trips/week |
|---|---|---|---|---|
| **3** | 80000 | 3 | 2.5 | 22 |
| **5** | 80000 | 3 | 2.5 | 24 |
| **6** | 80000 | 3 | 2.5 | 28 |
| **8** | 60000 | 4 | 2 | 28 |
| **9** | 80000 | 4 | 2 | 16 |
| **10** | 60000 | 3 | 2.5 | 11 |
| **11** | 80000 | 6 | 2.5 | 20 |
| **12** | 80000 | 3 | 2.5 | 31 |
| **13** | 80000 | 3 | 3 | 25 |
| **14** | 60000 | 3 | 2 | 28 |
| **15** | 60000 | 4 | 2 | 24 |
| **16** | 60000 | 3 | 2 | 24 |
| **17** | 60000 | 4 | 3 | 19 |
| **18** | 80000 | 3 | 2 | 29 |
| **19** | 60000 | 4 | 3.5 | 20 |
| **21** | 80000 | 3 | 2.5 | 28 |
| **22** | 80000 | 4 | 2.5 | 34 |
| **111** | 80000 | 1 | 2 | 11 |
| **112** | 60000 | 3 | 2 | 11 |
| **113** | 60000 | 3 | 2 | 12 |
| **114** | 60000 | 2 | 2 | 11 |
| **115** | 60000 | 4 | 2.5 | 18 |
| **116** | 60000 | 4 | 2.5 | 17 |
| | | | Average no. of trips/week = | 21.34 |

Total number of households in the HIHV category = 23

According to the cross-classification model, the total number of trips generated/ week by the 127 nos. of household,

$$T_i = 59 \times 18.01 + 37 \times 26.02 + 8 \times 13.12 + 23 \times 21.34$$

$$= 2622 \text{ (approx.)}$$

## 3.2 Regression model

In Regression model, a linear relationship is assumed to exist between the number of trips generated and the factor that affect the trip generation process. By using this model, determination of the trip generation becomes simpler once the parameters associated with the regression functions are known.

The same data is used for fitting a mathematical relationship between the independent variables and the dependent variables. In case of trip generation, the dependent variable is the number of trips generated/week and the independent variables are the factors affecting the trip generation such as- household size, income level, vehicle ownership, etc.

Linear regression analysis of the data of 127 nos. of households is carried out in Microsoft Excel-2007. The dependent variable chosen for the analysis are income, household size and vehicle ownership in terms of PCUs. The equation is in the form of,

$$T_i = \alpha_1 z_1 + \alpha_2 z_2 + \alpha_3 z_3 + U$$

Where, U is the disturbance term, which is a constant. $\alpha_1$, $\alpha_2 and\ \alpha_3$ are the regression coefficient obtained for the linear regression analysis carried out and z1, z2 and z3 are the independent variables, income, household size and vehicle ownership respectively.

The values of the regression coefficients and the disturbance term along with the standard error are given in table 6.

Table 6: Results of Linear Regression Analysis

| | *Coefficients* | *Standard Error* |
|---|---|---|
| Intercept | 12.18592561 | 3.609084223 |
| Income (`) | -7.24636E-05 | 5.36138E-05 |
| Household size(>3years) | 0.721496841 | 0.492362159 |
| vehicle ownership ( PCU) | 5.166802106 | 1.090282495 |

Therefore, the equation for the no. of trips is,

$$T_i = 12.18 - 0.000072 \times \text{income} + 0.72 \times \text{household size} + 5.16 \times \text{vehicle ownership}$$

Table 7 below shows the comparison between the data obtained from the survey and the predicted number of trips obtained from the relationship we got by applying linear regression analysis on the data obtained. From the table it can be clearly seen that the predicted number of trip/week which is obtained from the regression equation is exactly equal to the sum of the total no.of trips/week obtained from the survey.

Table 7: Comparison of the observed and Predicted No. of trips

| **Observations** | **Observed No.of trips/week** | **Predicted no.of trips/week** | **Residuals** |
|---|---|---|---|
| 1 | 10 | 17.0250312 | -7.025031195 |
| 2 | 13 | 10.41523541 | 2.584764594 |
| 3 | 22 | 21.47033646 | 0.52966354 |
| 4 | 3 | 16.30353435 | -13.30353435 |
| 5 | 24 | 21.47033646 | 2.52966354 |
| 6 | 28 | 21.47033646 | 6.52966354 |
| 7 | 17 | 18.47430243 | -1.47430243 |
| 8 | 28 | 21.05770348 | 6.942296517 |

| Observations | Observed No.of trips/week | Predicted no.of trips/week | Residuals |
|---|---|---|---|
| 9 | 16 | 19.60843225 | -3.608432248 |
| 10 | 11 | 22.91960769 | -11.91960769 |
| 11 | 20 | 23.63482698 | -3.634826984 |
| 12 | 31 | 21.47033646 | 9.52966354 |
| 13 | 25 | 24.05373751 | 0.946262487 |
| 14 | 28 | 20.33620664 | 7.663793359 |
| 15 | 24 | 21.05770348 | 2.942296517 |
| 16 | 24 | 20.33620664 | 3.663793359 |
| 17 | 19 | 26.22450559 | -7.224505589 |
| 18 | 29 | 18.88693541 | 10.11306459 |
| 19 | 20 | 28.80790664 | -8.807906642 |
| 20 | 9 | 19.19579927 | -10.19579927 |
| 21 | 28 | 21.47033646 | 6.52966354 |
| 22 | 34 | 22.1918333 | 11.8081667 |
| 23 | 22 | 12.99863646 | 9.001363541 |
| 24 | 19 | 15.58203751 | 3.417962488 |
| 25 | 12 | 16.19976524 | -4.199765242 |
| 26 | 14 | 22.80956103 | -8.80956103 |
| 27 | 35 | 20.64507051 | 14.35492949 |
| 28 | 20 | 20.64507051 | -0.645070506 |
| 29 | 18 | 22.80956103 | -4.80956103 |
| 30 | 18 | 26.53336945 | -8.533369453 |
| 31 | 16 | 19.92357366 | -3.923573664 |
| 32 | 14 | 17.34017261 | -3.340172612 |
| 33 | 41 | 29.41935682 | 11.58064318 |

| Observations | Observed No.of trips/week | Predicted no.of trips/week | Residuals |
|---|---|---|---|
| 34 | 14 | 20.64507051 | -6.645070506 |
| 35 | 25 | 25.09037577 | -0.09037577 |
| 36 | 19 | 25.39296208 | -6.392962083 |
| 37 | 18 | 19.92357366 | -1.923573664 |
| 38 | 14 | 20.64507051 | -6.645070506 |
| 39 | 18 | 20.64507051 | -2.645070506 |
| 40 | 18 | 19.20207682 | -1.202076823 |
| 41 | 18 | 18.06166945 | -0.061669453 |
| 42 | 25 | 25.09037577 | -0.09037577 |
| 43 | 14 | 18.78316629 | -4.783166294 |
| 44 | 31 | 27.97636314 | 3.023636864 |
| 45 | 24 | 25.09037577 | -1.09037577 |
| 46 | 16 | 21.78547788 | -5.785477876 |
| 47 | 30 | 19.92357366 | 10.07642634 |
| 48 | 16 | 22.50697472 | -6.506974717 |
| 49 | 18 | 25.09037577 | -7.09037577 |
| 50 | 14 | 17.34017261 | -3.340172612 |
| 51 | 14 | 18.06166945 | -4.061669453 |
| 52 | 12 | 16.61867577 | -4.61867577 |
| 53 | 12 | 27.97636314 | -15.97636314 |
| 54 | 20 | 20.64507051 | -0.645070506 |
| 55 | 28 | 23.22847156 | 4.771528441 |
| 56 | 18 | 19.20207682 | -1.202076823 |
| 57 | 24 | 20.64507051 | 3.354929494 |
| 58 | 30 | 26.53336945 | 3.466630547 |

| Observations | Observed No.of trips/week | Predicted no.of trips/week | Residuals |
|---|---|---|---|
| 59 | 12 | 18.48057998 | -6.480579982 |
| 60 | 24 | 19.92357366 | 4.076426336 |
| 61 | 13 | 18.06166945 | -5.061669453 |
| 62 | 19 | 19.92357366 | -0.923573664 |
| 63 | 10 | 18.06166945 | -8.061669453 |
| 64 | 13 | 23.22847156 | -10.22847156 |
| 65 | 15 | 20.64507051 | -5.645070506 |
| 66 | 35 | 19.92357366 | 15.07642634 |
| 67 | 30 | 17.34017261 | 12.65982739 |
| 68 | 30 | 18.78316629 | 11.21683371 |
| 69 | 25 | 17.34017261 | 7.659827388 |
| 70 | 24 | 21.06398103 | 2.936018965 |
| 71 | 25 | 25.09037577 | -0.09037577 |
| 72 | 28 | 17.34017261 | 10.65982739 |
| 73 | 35 | 23.22847156 | 11.77152844 |
| 74 | 40 | 29.83826735 | 10.16173265 |
| 75 | 36 | 22.50697472 | 13.49302528 |
| 76 | 26 | 19.92357366 | 6.076426336 |
| 77 | 27 | 27.67377682 | -0.673776823 |
| 78 | 25 | 22.50697472 | 2.493025283 |
| 79 | 38 | 22.50697472 | 15.49302528 |
| 80 | 42 | 23.9499684 | 18.0500316 |
| 81 | 40 | 22.08806419 | 17.91193581 |
| 82 | 20 | 15.89717893 | 4.102821071 |
| 83 | 25 | 26.53336945 | -1.533369453 |

| Observations | Observed No.of trips/week | Predicted no.of trips/week | Residuals |
|---|---|---|---|
| 84 | 15 | 15.89717893 | -0.897178929 |
| 85 | 22 | 22.50697472 | -0.506974717 |
| 86 | 25 | 22.50697472 | 2.493025283 |
| 87 | 15 | 14.75677156 | 0.243228441 |
| 88 | 18 | 17.34017261 | 0.659827388 |
| 89 | 20 | 22.50697472 | -2.506974717 |
| 90 | 18 | 19.20207682 | -1.202076823 |
| 91 | 15 | 16.61867577 | -1.61867577 |
| 92 | 20 | 20.64507051 | -0.645070506 |
| 93 | 30 | 25.81187261 | 4.188127388 |
| 94 | 28 | 22.50697472 | 5.493025283 |
| 95 | 10 | 12.59228103 | -2.592281034 |
| 96 | 16 | 19.92357366 | -3.923573664 |
| 97 | 15 | 16.61867577 | -1.61867577 |
| 98 | 14 | 17.34017261 | -3.340172612 |
| 99 | 18 | 22.50697472 | -4.506974717 |
| 100 | 16 | 19.92357366 | -3.923573664 |
| 101 | 20 | 18.06166945 | 1.938330547 |
| 102 | 26 | 25.09037577 | 0.90962423 |
| 103 | 16 | 14.75677156 | 1.243228441 |
| 104 | 18 | 19.92357366 | -1.923573664 |
| 105 | 12 | 15.89717893 | -3.897178929 |
| 106 | 50 | 22.50697472 | 27.49302528 |
| 107 | 16 | 27.67377682 | -11.67377682 |
| 108 | 30 | 21.78547788 | 8.214522124 |

| Observations | Observed No.of trips/week | Predicted no.of trips/week | Residuals |
|---|---|---|---|
| 109 | 28 | 22.50697472 | 5.493025283 |
| 110 | 12 | 14.02899717 | -2.028997165 |
| 111 | 11 | 17.44394172 | -6.443941724 |
| 112 | 11 | 20.33620664 | -9.336206641 |
| 113 | 12 | 20.33620664 | -8.336206641 |
| 114 | 11 | 19.6147098 | -8.6147098 |
| 115 | 18 | 23.64110454 | -5.641104536 |
| 116 | 17 | 23.64110454 | -6.641104536 |
| 117 | 11 | 16.61867577 | -5.61867577 |
| 118 | 17 | 17.34017261 | -0.340172612 |
| 119 | 17 | 15.89717893 | 1.102821071 |
| 120 | 17 | 15.89717893 | 1.102821071 |
| 121 | 18 | 23.22847156 | -5.228471559 |
| 122 | 10 | 17.34017261 | -7.340172612 |
| 123 | 11 | 18.06166945 | -7.061669453 |
| 124 | 11 | 17.34017261 | -6.340172612 |
| 125 | 19 | 29.83826735 | -10.83826735 |
| 126 | 17 | 15.89717893 | 1.102821071 |
| 127 | 12 | 17.34017261 | -5.340172612 |
| TOTAL = | 2622 | 2622 | |

The trip generation model in general includes variables which give the number of potential trip-makers and tells about the possibility that a potential trip-maker will generate a trip. The above two models are based on the analysis of the empirical data collected and each time a new set of data is collected the entire analysis is to be revamped.

# Chapter -4

# Theory and Model Development

For the development of an efficient model, that can predict the number of trips to be generated from a particular zone, application of fuzzy logic is preferred as it can capture the vagueness of the human mind. It can also predict the possibility of a potential trip-maker to make a trip as it is a linguistic tool, unlike the classical mathematical models.

## 4.1 Fuzzy Sets

A collection of similar elements having same type of properties is known as a set. A set is known as a crisp set when the belongingness of the member of the set to the sets is complete, i.e. one can clearly say that the element belongs to a particular set. A crisps set is defined as,

$$A = \{x, x \in X\}$$

Where, $x$ is a member of the set $X$ and shares the common property with all the other members of the set $X$.

Zadeh in 1965 introduced the concept of fuzzy sets.[6] Since then, it has found its application is a very vast field. In a fuzzy set, the belongingness of an element to a set is not complete. i.e. they can belong to any other set simultaneously either partially or fully belonging to any other set. This is where it differs from a classical set. In fuzzy set, the membership function of an element defines its belongingness to the set and it can acquire any value between 0 & 1 whereas in case of the classical crisp sets, there is nothing like this. If an element shares the same properties as of the other members of the set, then it belongs to the set, otherwise not.

This is where a fuzzy set is capable in capturing the vagueness of the human mind as the boundary of the set is not a crisp one rather it is a vague one.

A fuzzy set A is defined as,

$$A = \{x, \mu_A(x)\},$$

Where, $\mu_A(x)$ is the membership function of element x in set A. Its value lies between 0 & 1. The greater $\mu_A(x)$, the greater the truth of the statement that element x belongs to set A.[5]

## 4.2 Model Developed

Fuzzy inference is based on approximate reasoning and deals with the linguistic variables. According to Zadeh, fuzzy inference can deduce a possibly imprecise conclusion from the collection of imprecise variables.[6] The figure below shows a basic fuzzy inference system.

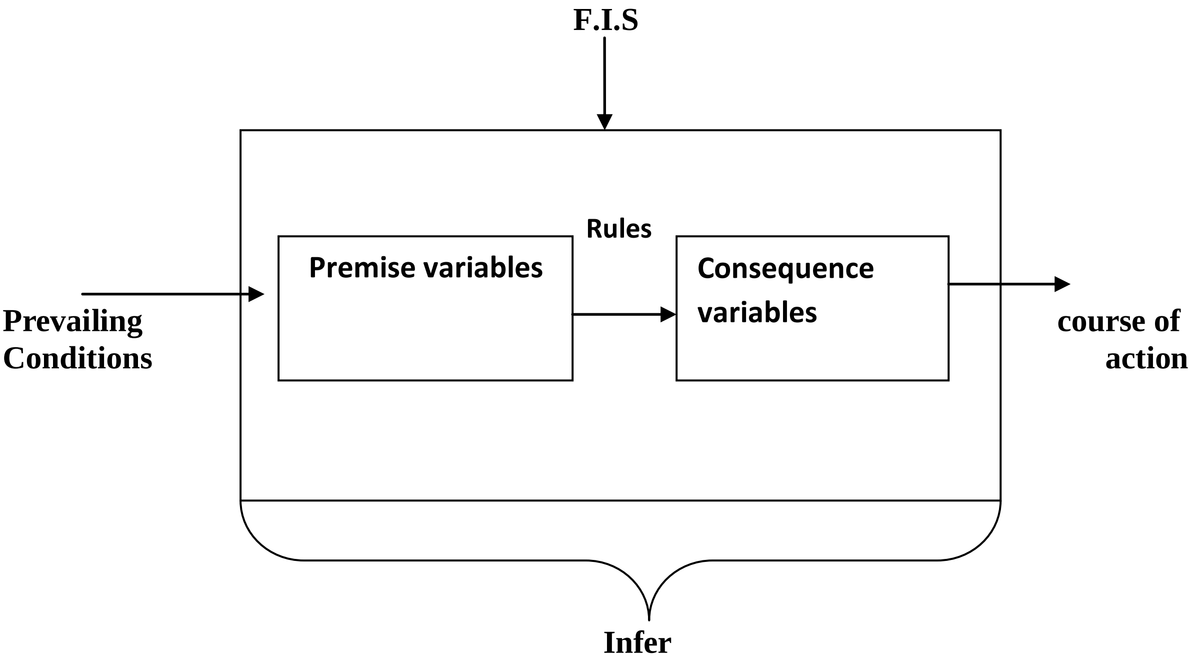


Figure 2: Fuzzy Inference System (adapted from Chattaraj. U and Panda .M 2010)

The various constituents of the fuzzy rule base are –

### 4.2.1 Proposition and Truth value

A proposition is a statement which is neither true nor false. In fuzzy logic the truth value of a proposition lies between 0 & 1. Propositions having a truth value of 1 are considered as true propositions and that having 0 are considered as false propositions. Rest all propositions have truth values between 0 & 1.[5]

### 4.2.2 Logical Connectives

Logical Connectives are used for connecting more than propositions. AND and OR are the two basic logical connectives used in fuzzy rule.

### 4.2.3 Premise Variables

It is basically the input given to the fuzzy inference. It can certainly carry a value but that value does not guarantee its grouping. Premise variables are basically propositions which are represented linguistically according to the prevailing conditions.

The assumed classes of premise variables and their membership functions are as follows:

#### 4.2.3.1 Age

The linguistic variables for age (A) are expressed in three groups, namely young, middle aged and old.

The membership function $\mu_{yng}(a_z)$, describing the set "young" is described as,

$$\mu_{yng}(a_z) = \begin{cases} 1; a_z \leq a_z^1 \\ \dfrac{a_z^2 - a_z}{a_z^2 - a_z^1}; \ a_z^1 < a_z \leq a_z^2 \\ 0; \ a_z > a_z^2 \end{cases}$$

Similarly, the membership function $\mu_{mag}(a_z)$ , describing the set "middle aged" is described as

$$\mu_{mag}(a_z) = \begin{cases} 0\,; a_z \le a_z^1 \\ \dfrac{a_z - a_z^1}{a_z^2 - a_z^1}\,; a_z^1 < a_z \le a_z^2 \\ \dfrac{a_z^3 - a_z}{a_z^3 - a_z^2}; a_z^2 < a_z \le a_z^3 \\ 0;\ a_z > a_z^3 \end{cases}$$

The membership function $\mu_{old}(a_z)$, describing the set “old” is described as

$$\mu_{old}(a_z) = \begin{cases} 0; a_z \le a_z^2 \\ \dfrac{a_z - a_z^2}{a_z^3 - a_z^2};\ a_z^2 < a_z \le a_z^3 \\ 1; a_z > a_z^3 \end{cases}$$

It may be noted that the values of the limits $a_z^1, a_z^2\ and\ a_z^3$ can be decided through a trial and error process. The overall membership function for the age set is shown in figure 3.

### 4.2.3.2 Income

The linguistic variable for income (I) is expressed in two groups namely low income group & high income group.

The membership function $\mu_{lin}(i_z)$, describing the set “low income group” can be described as

$$\mu_{lin}(i_z) = \begin{cases} 1;\ i_z \le i_z^1 \\ \dfrac{i_z - i_z^1}{i_z^2 - i_z^1}; i_z^1 < i_z \le i_z^2 \\ 0; i_z > i_z^2 \end{cases}$$

Similarly, the membership function $\mu_{hin}(i_z)$, describing the set “high income group” can be described as

$$\mu_{hin}(i_z) = \begin{cases} 0; i_z \le i_z^1 \\ \dfrac{i_z - i_z^1}{i_z^2 - i_z^1};\ i_z^1 < i_z \le i_z^2 \\ 1; i_z > i_z^2 \end{cases}$$

Again the values of the limits $i_z^1 and\ i_z^2$ can be obtained by trial and error method. The overall membership function for the income set is shown in figure 4.

### 4.2.3.3 Vehicle Ownership:

The linguistic variable for vehicle ownership (O) is expressed in two groups namely low ownership & high ownership.

The membership function $\mu_{low}(o_z)$, describing the set "low ownership group" can be described as

$$\mu_{low}(o_z) = \begin{cases} 1;\ o_z \le o_z^1 \\ \dfrac{o_z - o_z^1}{o_z^2 - o_z^1};\ o_z^1 < o_z \le o_z^2 \\ 0;\ o_z > o_z^2 \end{cases}$$

Similarly, the membership function $\mu_{hog}(o_z)$, describing the set "high ownership group" can be described as

$$\mu_{hog}(o_z) = \begin{cases} 0;\ o_z \le o_z^1 \\ \dfrac{o_z - o_z^1}{o_z^2 - o_z^1};\ o_z^1 < o_z \le o_z^2 \\ 1;\ o_z > o_z^2 \end{cases}$$

Again the values of the limits $o_z^1 and\ o_z^2$ can be obtained by trial and error method. The overall membership function for the vehicle ownership set is shown in figure 5.

### 4.2.4 Consequence Variable:

A consequence variable is a fuzzy number representing the approximate value of the course of action, which is approximately equal to a value. It is calculated after the imposition of certain prevailing conditions on the premise variables. If the prevailing conditions are such that, satisfy the compatibility with the premise variables of more than one rule, the course of action is determined by the weighted average of the consequence variables of all those rules.[5]

The consequence variables for the assumed linguistic variables are as follows:

#### 4.2.4.1 Age

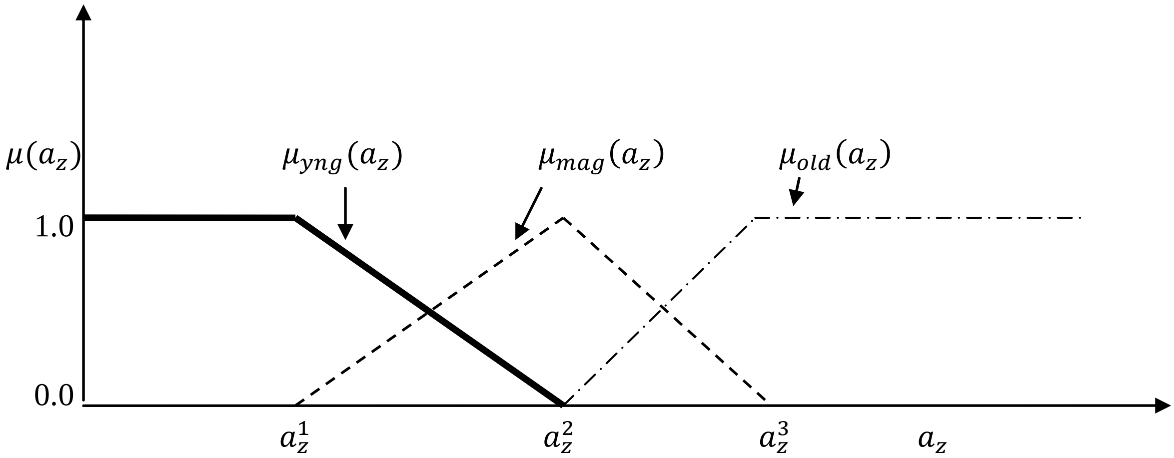


Figure 3: Membership function for the set Age

#### 4.2.4.2 Income

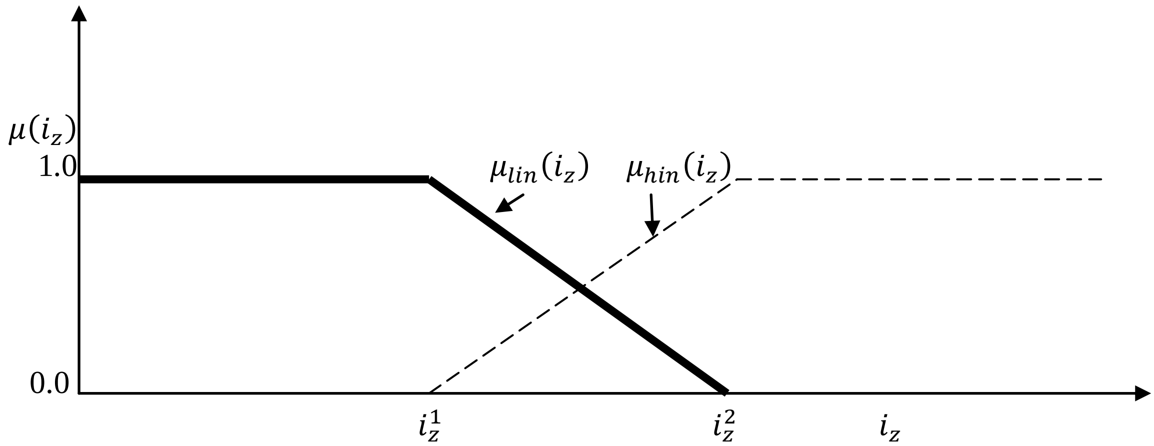


Figure 4: Membership function for the set Income

### 4.2.4.3 Vehicle Ownership

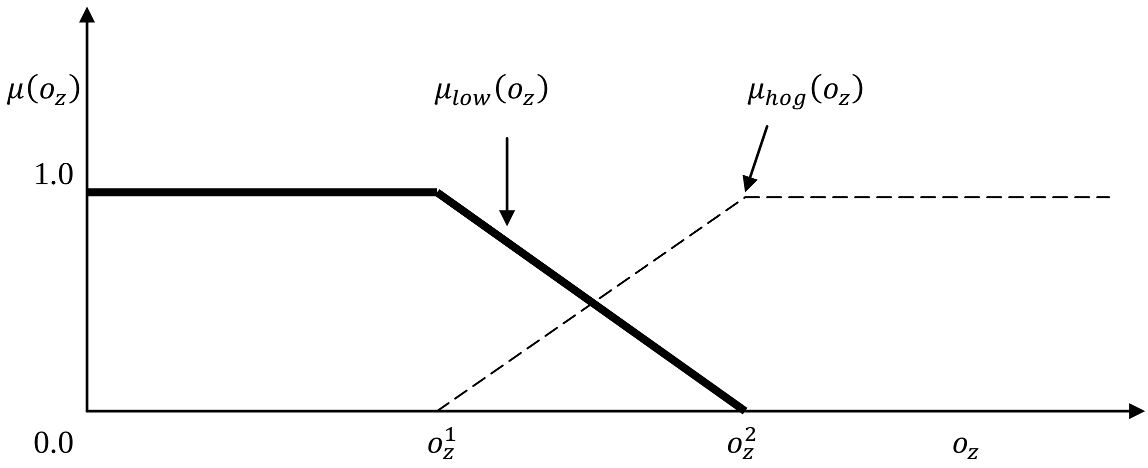


Figure 5: Membership function for the vehicle ownership set

## 4.2.5 Rules:

All the three premise variables are classified into two or three groups. The rules are formed by applying combinational of the groups. The number of groups that are to be formed can be determined by multiplying the number of groups in each premise variable.ie)(3 x 2 x 2 =12). The general form of the rules is shown below.

If Age is $\boldsymbol{A}_1$ AND Income is $\boldsymbol{I_1}$ AND vehicle ownership is $\boldsymbol{O_1}$ THEN conclusion is $\boldsymbol{\rho_1}$.

If Age is $\boldsymbol{A}_1$ AND Income is $\boldsymbol{I_1}$ AND vehicle ownership is $\boldsymbol{O_2}$ THEN conclusion is $\boldsymbol{\rho_2}$.

If Age is $\boldsymbol{A}_1$ AND Income is $\boldsymbol{I_2}$ AND vehicle ownership is $\boldsymbol{O_1}$ THEN conclusion is $\boldsymbol{\rho_3}$.

… … … … …

… … … … …

If Age is $\boldsymbol{A}_3$ AND Income is $\boldsymbol{I_2}$ AND Vehicle ownership is $\boldsymbol{O_2}$ THEN conclusion is $\boldsymbol{\rho_{12}}$.

The consequence of each rule is unique and is obtained from the analysis of the field data. A given set of input may fall in more than one rule and the subsequent output is the weighted average of all the rules.

### 4.2.6 Output (Conclusion, D(k)):

Weighted average method is used to obtain the conclusion of the input set. Since the premise variables are connected using AND the weight of a membership set is the smallest value among the elements in a particular membership subset.

Weight of a membership subset, $w_{r,k}=\min\{\mu_r(A_k), \mu_r(O_k), \mu_r(I_k)\}$

Where $1 \leq r \leq 12$

The calculation for the weighted average method is shown below.

Let D (k) be the conclusion of the input set. D (k) is given by

$$\mathbf{D(k)}=\sum_{r=1}^{12}\left(\frac{w_{r,k}\cdot\rho_r}{\sum_{r=1}^{12} w_{r,k}}\right)$$

Where, $w_{r,k}$ is the weight of the $r^{th}$ membership Subset with input set k.

$\boldsymbol{\rho}_r$ is the consequence $r^{th}$ membership subset.

# Chapter 5

# Result and Discussion

A model was developed using the fuzzy logic to calculate the no. of trips that an individual can generate based on the variable like the individual's age, income and vehicle ownership. The model was developed using the language C++. For the sake of calibration of the model half of data used for the empirical calculation is used. For the calibration of the model the method of least square sum of errors was used. After the calibration of the model, another model was developed that itself generates the input data for 1000 individuals and then calculate the number of trips generated by each individual. The limits of the membership functions found after calibration of the model are shown in table 8. These limits were found by using trial and error method on half of the data.

Table 8: Values of the Limits obtained from trial and error method

| **Limits** | **Values** |
|---|---|
| **Age limit, $a_z^1$** | 15 |
| **Age limit, $a_z^2$** | 35 |
| **Age limit, $a_z^3$** | 50 |
| **Income limit, $i_z^1$** | 10000 |
| **Income limit, $i_z^2$** | 21000 |
| **Vehicle ownership limit, $o_z^1$** | 0.5 |
| **Vehicle ownership limit, $o_z^2$** | 1.5 |

A basic flowchart of the model for 1000 nos. of individuals developed is shown below.

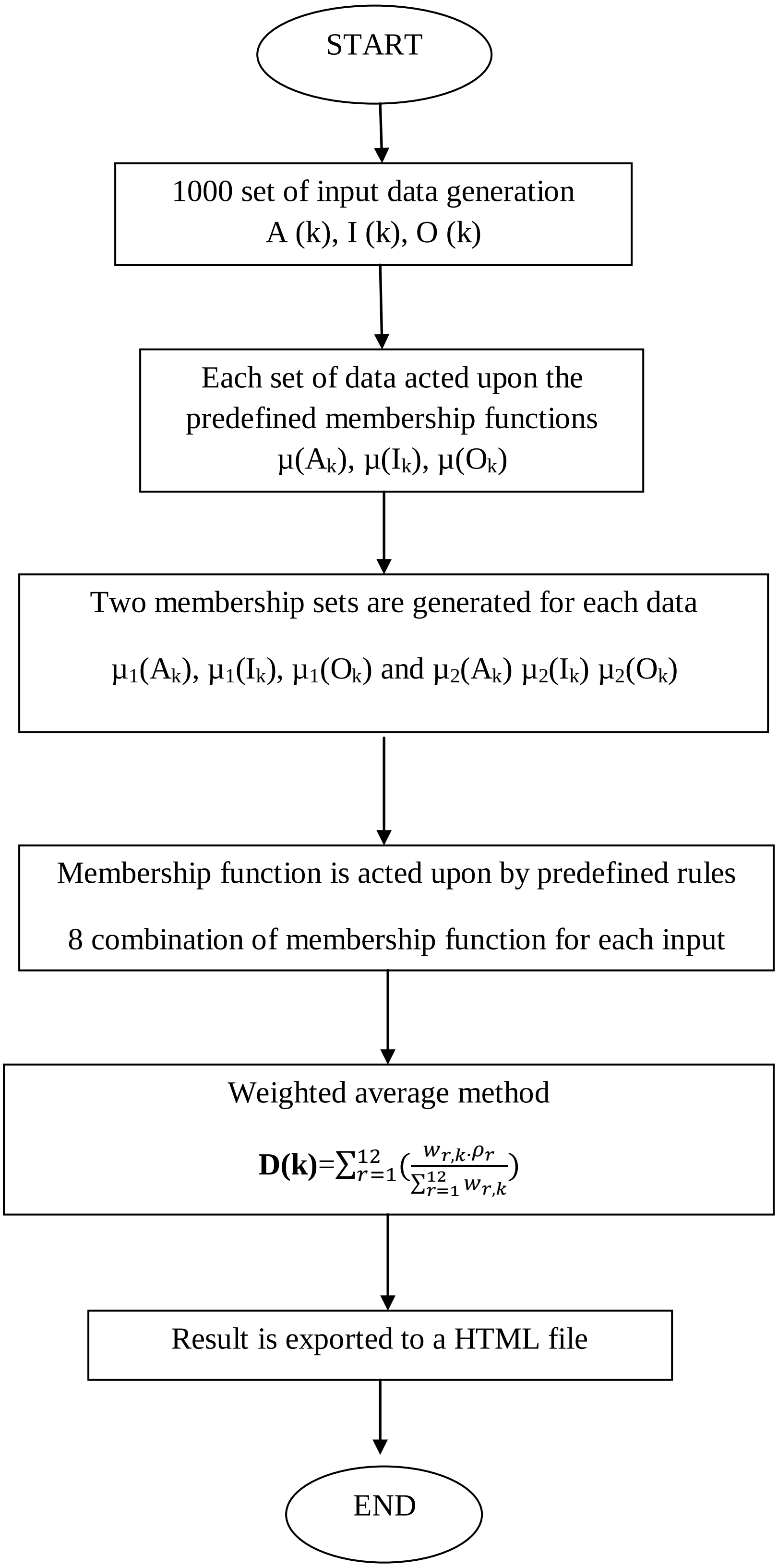


Figure 6: Basic Flowchart of the developed model

After, the calibration of the model by using half the data points, the model is validated by using the rest half of the data points. Table 9 shows the comparison of the no. of trips obtained from the field survey and the number of trips obtained from the developed model.

Table 9: Comparison of result obtained from the model with observed data

| Household no. | Average Age | Average Income | Vehicle ownership | observed no. of trip/ week | No. of trips/week from model |
|---|---|---|---|---|---|
| 1 | 37 | 20000 | 1.5 | 10 | 25.302 |
| 2 | 50 | 40000 | 0.5 | 13 | 12 |
| 3 | 43 | 27000 | 2.5 | 22 | 21.066 |
| 4 | 60 | 27000 | 1.5 | 3 | 10 |
| 5 | 42 | 28000 | 2.5 | 24 | 21.93 |
| 6 | 40 | 28000 | 2.5 | 28 | 23.66 |
| 7 | 35 | 15000 | 1.5 | 17 | 25.81 |
| 8 | 30 | 16000 | 2 | 28 | 22.95 |
| 9 | 46 | 16000 | 2 | 16 | 19.122 |
| 10 | 36 | 20000 | 2.5 | 11 | 26.208 |
| 11 | 41 | 15000 | 2.5 | 20 | 21.23 |
| 12 | 30 | 28000 | 2.5 | 31 | 25.5 |
| 13 | 40 | 28000 | 3 | 25 | 23.66 |
| 14 | 40 | 20000 | 2 | 28 | 23.1 |
| 15 | 30 | 15000 | 2 | 24 | 22.71 |
| 16 | 32 | 20000 | 2 | 24 | 25.42 |
| 17 | 25 | 15000 | 3 | 19 | 21.16 |
| 18 | 36 | 28000 | 2 | 29 | 27.13 |
| 19 | 30 | 15000 | 3.5 | 20 | 22.71 |
| 20 | 20 | 8000 | 1.5 | 35 | 17.25 |
| 21 | 18 | 8000 | 1.5 | 20 | 16.35 |
| 22 | 19 | 8000 | 1 | 14 | 15.92 |
| 23 | 18 | 8000 | 1.5 | 14 | 16.35 |
| 24 | 30 | 10000 | 2.5 | 25 | 21.75 |
| 25 | 20 | 10000 | 1.5 | 18 | 17.25 |
| 26 | 18 | 8000 | 1.5 | 14 | 16.35 |
| 27 | 46 | 8000 | 1.5 | 18 | 18.13 |
| 28 | 32 | 13000 | 1.5 | 18 | 23.1 |
| 29 | 29 | 8000 | 1 | 18 | 18.81 |
| 30 | 25 | 10000 | 2.5 | 25 | 19.5 |
| 31 | 21 | 8000 | 1 | 14 | 16.68 |
| 32 | 24 | 10000 | 2.5 | 24 | 19.05 |
| 33 | 22 | 14000 | 2 | 16 | 20.17 |
| 34 | 27 | 10000 | 1.5 | 30 | 20.4 |
| 35 | 28 | 10000 | 2 | 16 | 20.85 |
| 36 | 28 | 10000 | 2.5 | 18 | 20.85 |

| Household no. | Average Age | Average Income | Vehicle ownership | observed no. of trip/ week | No. of trips/week from model |
|---|---|---|---|---|---|
| 37 | 35 | 10000 | 1 | 14 | 22 |
| 38 | 20 | 8000 | 1 | 14 | 16.33 |
| 39 | 32 | 13000 | 1 | 12 | 21.25 |
| 40 | 23 | 8000 | 1.5 | 20 | 18.6 |
| 41 | 34 | 8000 | 2 | 28 | 23.55 |
| 42 | 31 | 13000 | 1.5 | 18 | 22.63 |
| 43 | 24 | 8000 | 1.5 | 24 | 19.05 |
| 44 | 33 | 20000 | 1.5 | 12 | 25.84 |
| 45 | 25 | 10000 | 1.5 | 24 | 19.5 |
| 46 | 21 | 8000 | 1 | 13 | 16.68 |
| 47 | 23 | 10000 | 1.5 | 19 | 18.6 |
| 48 | 26 | 8000 | 1 | 10 | 17.97 |
| 49 | 23 | 8000 | 2 | 13 | 18.6 |
| 50 | 19 | 8000 | 1.5 | 15 | 16.8 |
| 51 | 25 | 10000 | 1.5 | 35 | 19.5 |
| 52 | 40 | 27000 | 2.5 | 28 | 23.66 |
| 53 | 32 | 21000 | 2.5 | 34 | 26.5 |
| 54 | 39 | 32000 | 1 | 22 | 21.97 |
| 55 | 38 | 33000 | 1.5 | 19 | 25.4 |
| 56 | 41 | 15000 | 2.5 | 20 | 21.23 |
| 57 | 30 | 28000 | 2.5 | 31 | 25.5 |
| 58 | 32 | 20000 | 2 | 22 | 25.42 |
| 59 | 25 | 15000 | 3 | 17 | 21.16 |
| 60 | 30 | 16000 | 2 | 28 | 22.95 |
| 61 | 46 | 16000 | 2 | 18 | 19.12 |
| 62 | 36 | 20000 | 2.5 | 12 | 26.02 |
| | | | TOTAL | 1251 | 1295.258 |

From the comparison of field data with result from model, it can be seen that the model is properly calibrated and validated.

## Conclusion-

- By application of fuzzy logic, the vagueness of the human mind regarding the trip decision is captured.
- For calibration the empirical field data is used and by application of trial and error method, the values of the limits are found out.
- The model is successfully validated by comparing its result with the field data.

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